New results and method in AGN X-ray power spectra

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NGC 4051 - Credit: ESA/Hubble & NASA, D. Crenshaw and O. Fox

University of Leicester

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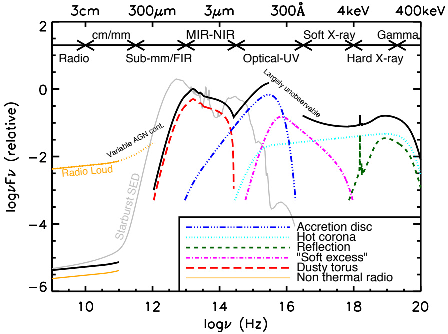
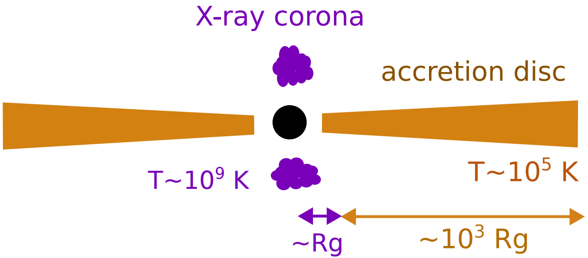
- Wavebands probe different regions



Spectral energy distribution of an AGN. Harrison+2014

The inner region of active galaxies

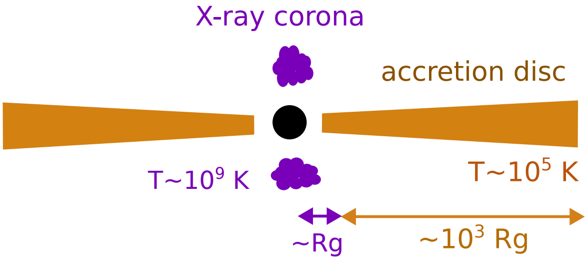


where one gravitational radius is given by:
$R_g \simeq 1.5(M/M_\odot)$ km

The inner region of active galaxies

Scope of this study:

- unabsorbed AGN, mostly Seyfert 1 galaxies
- soft X-rays: $0.3 - 1.5$ keV
- timing study: light curves.



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Astronomical light curves

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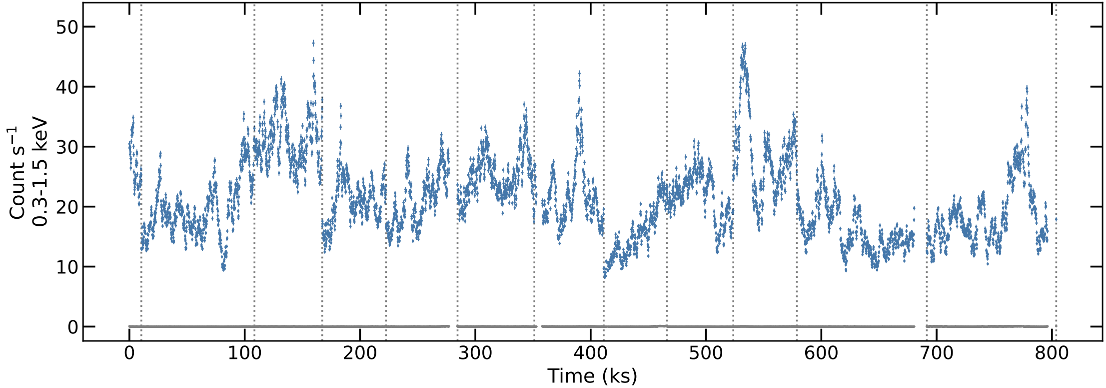
- Fluxes can be point sampled (optical, radio data)
- or obtained by binning recorded events on a detector (X-ray)
- an uncertainty is usually associated, it can be different between values (heteroscedasticity)
- gaps, irregular sampling are not uncommon: seasonal visibility...

Ark 564: a variable narrow-line Seyfert 1



Concatenated *XMM–Newton* light curves of Ark 564 from 2000 to 2022.

The stochastic variability of AGN

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We use second-order statistics to characterise the process: power spectral density

→ Describes how the variability is distributed over frequency (1/timescale)

→ Fourier transform of the autocovariance

Estimating variability power spectra

Formal definition of the power spectrum

$$\mathscr{P}(f) = \lim_{T\to+\infty} \frac{\mathbb{E}\left\{\left|\int_{-T}^{T} x(t)\, e^{-2\mathrm{i}\pi f t} \mathrm{d}t\right|^2\right\}}{2T}$$

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In practice, we use the periodogram:

$$P[f_j] = \frac{1}{n}\left|\sum_{i=1}^{n} x[t_i]\mathrm{e}^{-2\pi\mathrm{i} f_j t_i}\right|^2$$

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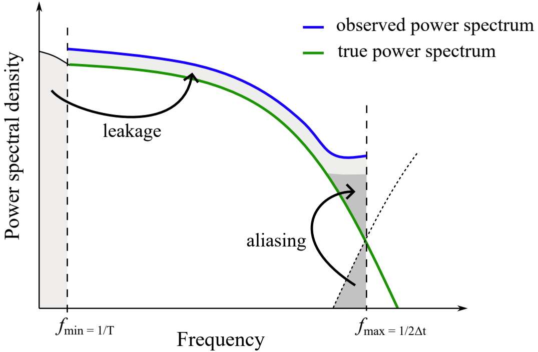
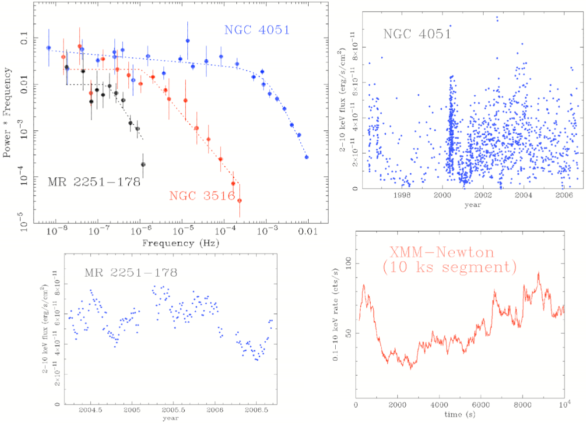
A biased and inconsistent estimator for $\mathscr{P}(f)$.



Biases of the periodogram.

Variability power spectra of active galaxies



Periodograms and light curves (Uttley+2007).

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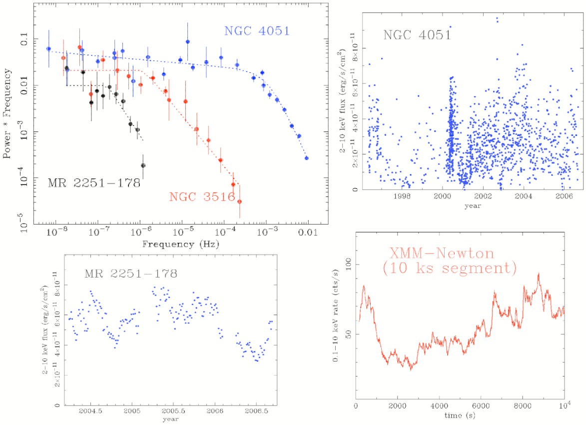

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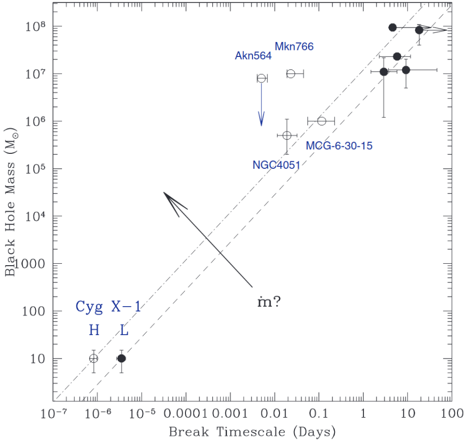
AGN power spectra are well-modelled with a power-law $f^{-\alpha}$

- flat at low frequencies: $\alpha \sim 0-1$
- bends to a steeper slope $\alpha > 2$ at high-frequencies

Timescales in power spectra of active galaxies



X-ray variability plane (McHardy+2004).

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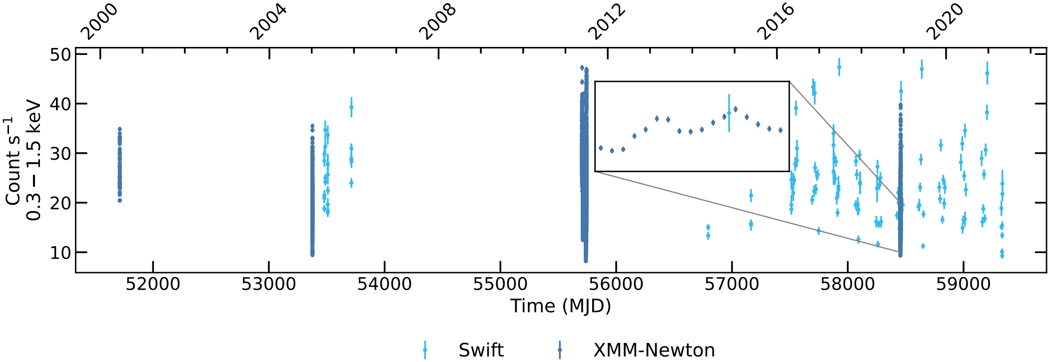

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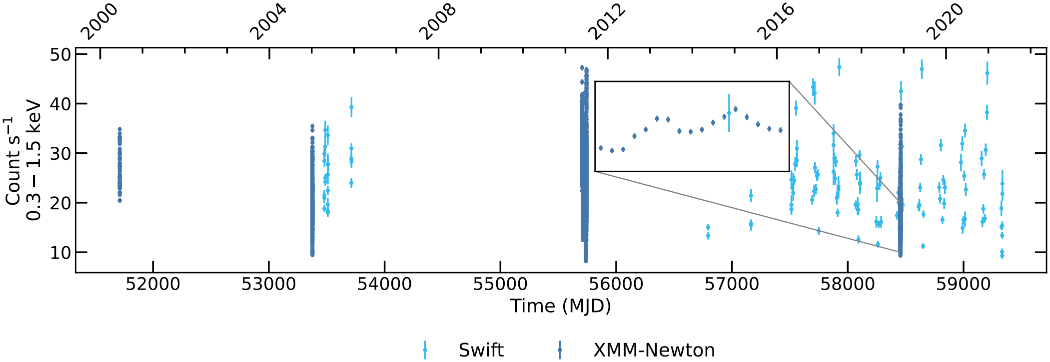

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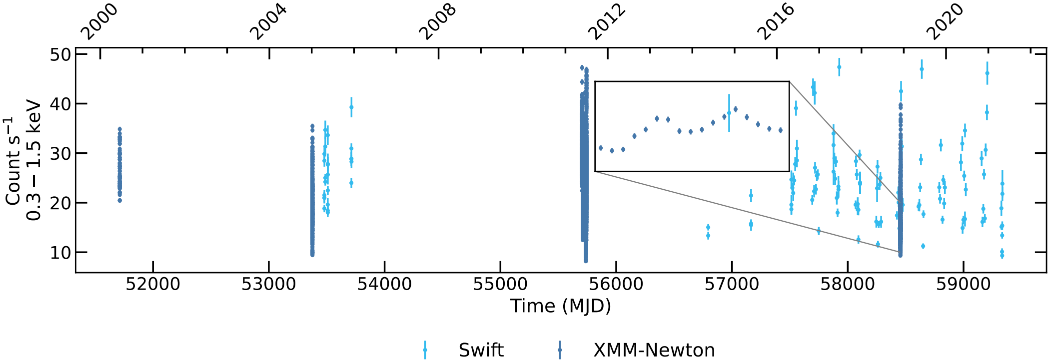

Swift and *XMM–Newton* light curves of Ark 564.

→ **Irregular sampling with large gaps** → **Cannot use standard Fourier methods!**

An important property of the power spectrum

Theorem

The power spectral density and the autocovariance function are Fourier pairs.

$$\mathscr{P}(f) = \int_{-\infty}^{+\infty} \mathscr{R}(\tau) e^{-2\mathrm{i}\pi f \tau} \mathrm{d}\tau \qquad \mathscr{R}(\tau) = \int_{-\infty}^{+\infty} \mathscr{P}(f) e^{2\mathrm{i}\pi f \tau} \mathrm{d}f. \tag{1}$$

Gaussian processes

Definition

A Gaussian process (GP) is a stochastic process where the joint probability distribution is a multivariate Gaussian distribution (Rasmussen&Williams+2006).

$$p_{\boldsymbol{Y}}(\boldsymbol{x}|\boldsymbol{m},\Sigma) = \frac{1}{(2\pi)^{n/2}|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(\boldsymbol{x}-\boldsymbol{m})^{\mathrm{T}}\Sigma^{-1}(\boldsymbol{x}-\boldsymbol{m})\right).$$

A GP is described by a mean $m(t)$ function and a covariance function (or autocovariance) $mathcalR(\tau)$. → here we assume that the mean function is a constant, $m(t) = \mu$

→ the covariance function $\mathscr{R}(\tau)$, is used to populate a covariance matrix $K_{ij} = \mathscr{R}(t_j - t_i)$

Inference with Gaussian processes

We can derive a log-likelihood function for the time series $\boldsymbol{y}$ with measurement errors $\boldsymbol{\sigma}$.
μ is the mean of the time series and ν quantities how good our measurement errors are.

$$\ln \mathscr{L}(\boldsymbol{\theta}, \nu, \mu) = -\frac{1}{2}\left(\boldsymbol{y}-\mu\right)^{\mathrm{T}}(K+\nu\boldsymbol{\sigma} I)^{-1}\left(\boldsymbol{y}-\mu\right) - \frac{1}{2}\ln|K+\nu\boldsymbol{\sigma} I| - \frac{n}{2}\ln(2\pi)$$

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→ structured covariance functions allow faster decompositions:

- State-space representation: Kalman recursions for CARMA (Kelly+2014)
- Quasi-separable algebra for `celerite` (Foreman-Makey+2017)

Comparison of current methods

Method	Flexibility[1]	Expressiveness[2]	Speed	Irregular sampling	Heteroscedasticity
Periodogram	n/a	+++	+++	-	-

[1] Variety of spectral shapes it can allow
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`celerite` (Foreman-Makey+2017)	+++	-	++	+++	+
`PIORAN` (Lefkir+2025)	++(+)	+++	++	+++	+

Estimating the power spectrum of irregular light curves

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PIORAN: a new time domain method

- Based on Gaussian process regression – immune to irregular sampling, allows for heteroscedasticity
- Uses the celerite algorithm for fast likelihood calculation (Foreman-Mackey+2017)
- Approximates power-law models: $\mathscr{P}(f) = \dfrac{A(f/f_b)^{-\alpha_1}}{1+(f/f_b)^{\alpha_2-\alpha_1}}$ with basis functions where $0 < \alpha_1 < 1$ and $2 < \alpha_2 < 6$.

The approximation

We use `celerite` covariance functions as basis functions:

SHO	$\psi_4(f) = \dfrac{1}{1+f^4}$	$\phi_4(\tau) = \dfrac{\pi}{\sqrt{2}} \exp\left(-\pi\sqrt{2}\tau\right)\left(\cos\left(\pi\sqrt{2}\tau\right) + \sin\left(\pi\sqrt{2}\tau\right)\right)$
DRW+Celerite	$\psi_6(f) = \dfrac{1}{1+f^6}$	$\phi_6(\tau) = \dfrac{\pi}{\sqrt{3}} \left(\dfrac{\exp\left(-2\pi\tau\right)}{\sqrt{3}} + \exp\left(-\pi\tau\right)\left(\dfrac{\cos(\pi\sqrt{3}\tau)}{\sqrt{3}} + \sin(\pi\sqrt{3}\tau)\right)\right)$

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Using $J = 20$ basis functions with f_j geometrically spaced from $f_{\mathrm{min}}/S_{\mathrm{low}}$ to $f_{\mathrm{max}}/S_{\mathrm{high}}$.
The approximation can be written as:

$$\tilde{\mathscr{P}}(f) = \sum_{j=0}^{J-1} a_j \psi(f/f_j) \qquad \tilde{\mathscr{R}}(\tau) = \sum_{j=0}^{J-1} a_j f_j \phi(\tau f_j)$$

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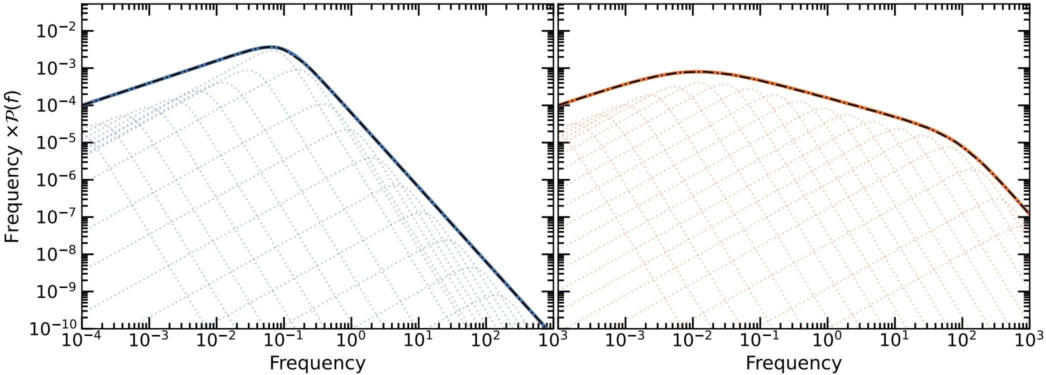
We can find a_j with the constraint:

$$\boldsymbol{p} = \boldsymbol{a}B \quad \text{where } B_{ij} = \psi(f_i/f_j) \text{ and } p_j = \mathscr{P}(f_j)$$

Visual representation of the approximation



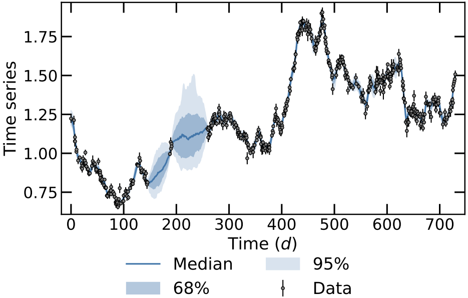
Approximated single-bending (left) and double-bending (right) model.

Parameters and priors

Modelling	Parameter	Description	Prior distribution
Power spectrum	α_1	Low-frequency slope	Uniform$[0, 1.25]$
	α_2	Intermediate slope	Uniform$[\alpha_1, \alpha_{\max}]$
	α_3	High-frequency slope	Uniform$[\alpha_2, \alpha_{\max}]$
	$f_{b,1}$	Low-frequency bend	Log-uniform$[f_{\text{start}}, f_{\text{stop}}]$
	$f_{b,2}$	High-frequency bend	Log-uniform$[f_{b,1}, f_{\text{stop}}]$
Time series	variance	Variance of the process	Log-normal$(-3, 2)$
	ν	Scale factor on the error bars	Gamma$(2, 0.5)$
	μ	Mean of the Gaussian time series	Normal$(\bar{x}, \beta s^2)$
	c	Offset for a log-normal time series	Log-uniform$\left[10^{-6}, 0.99 \min(\boldsymbol{x})\right]$
	γ	Intercalibration for two time series	Log-normal(-0.1,0.2)

Simulations

Now we can put everything together and try to do inference on simulated light curves:



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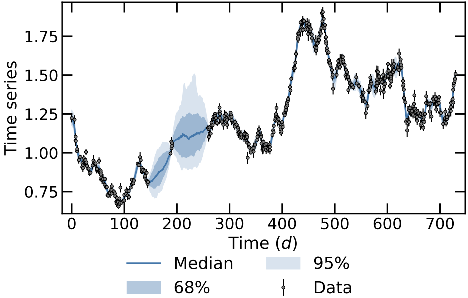

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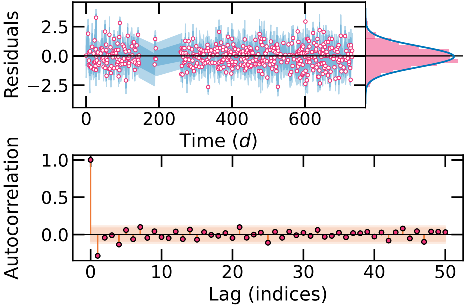
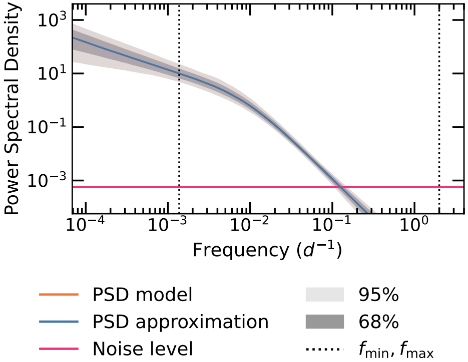


Diagnostics in the time domain

Posterior power spectrum



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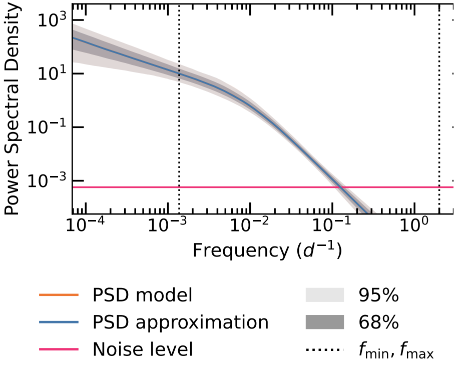

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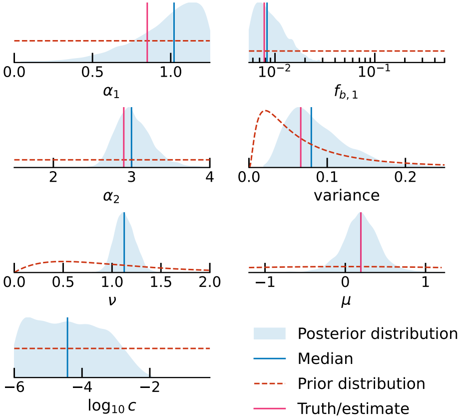
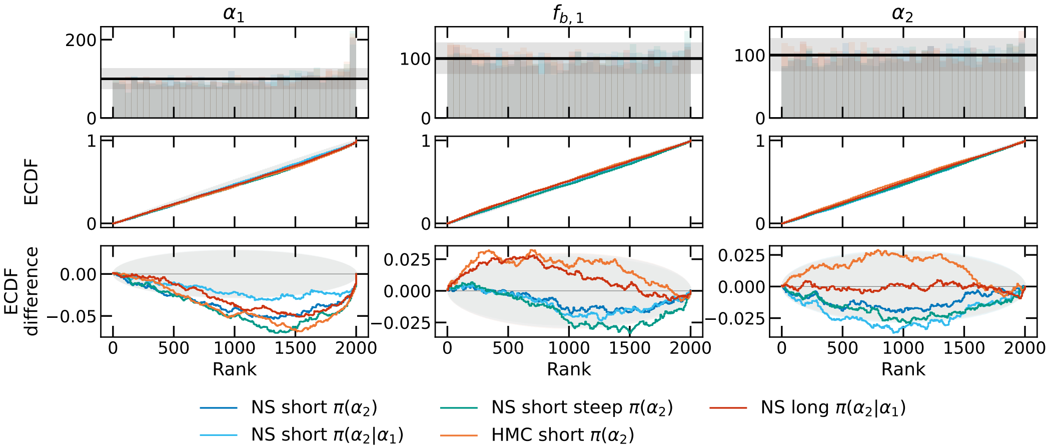


Distributions of the posterior samples

Simulation-based calibration (Talts et al. 2018)



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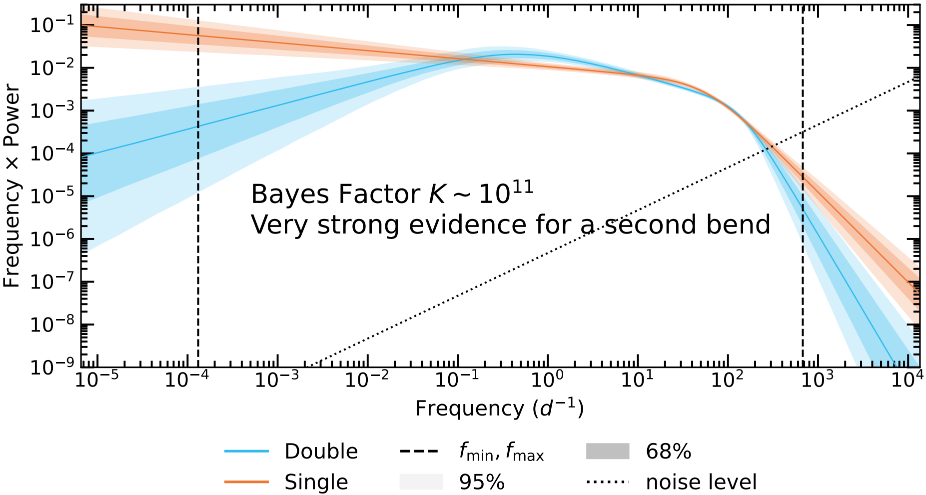
- Gaussian time series
  - Can account for the rms-flux relationship/lognormal distribution using a log transformation of the data
  - Modelling Poisson data (observation model) could be possible... but expensive!
- Weak-stationarity
  - Split the time series into segments if non-stationarity is suspected
  - Deep-State Space Gaussian processes (Zhao+2020) could also help?

The power spectrum of Ark 564



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- Possibility to model QPOs... at your own risk!
- Implementations in `stingray` (Python) and `Pioran.jl` (Julia)

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1. 56 variable Type-1 AGN with masses from $10^6 M_\odot$ to $2\times10^8 M_\odot$

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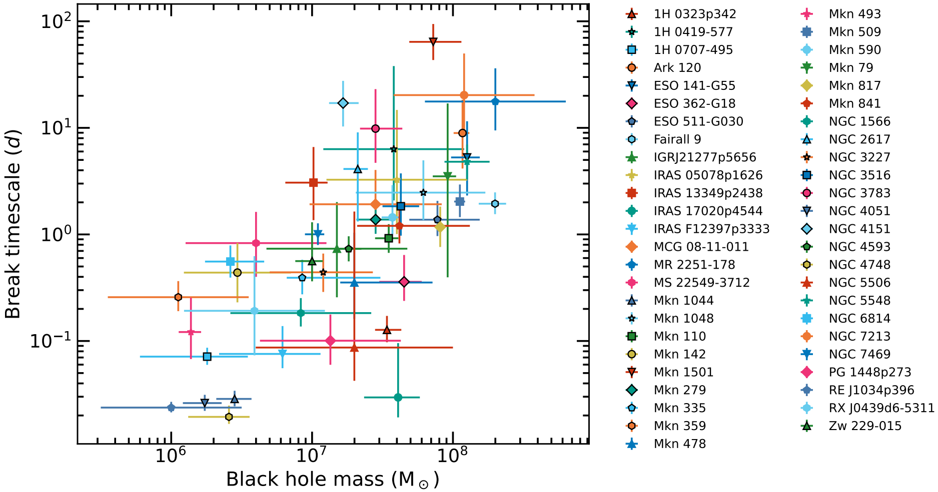
5. XMM-Newton (EPIC-pn) light curves binned to 150s

The X-ray variability plane



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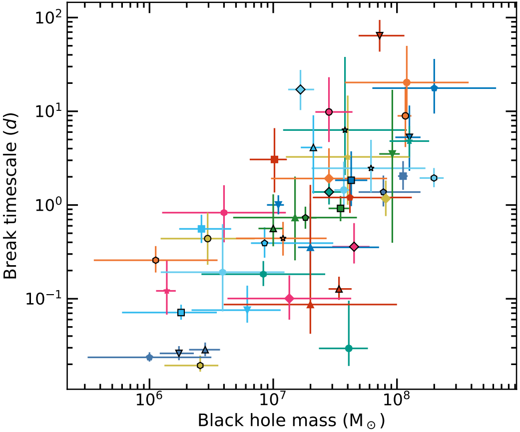

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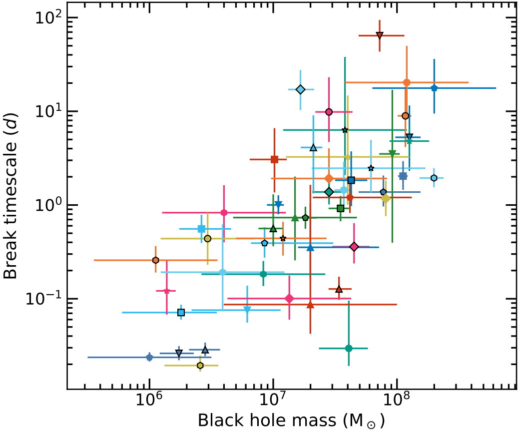

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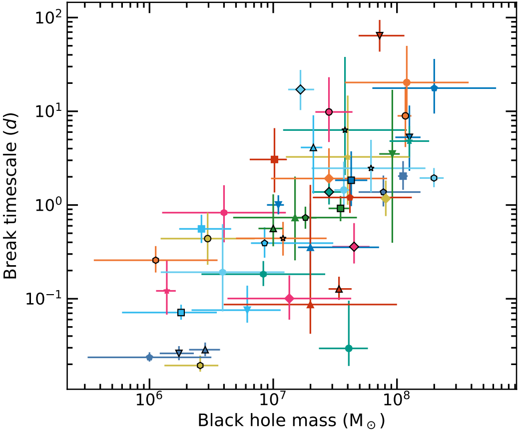

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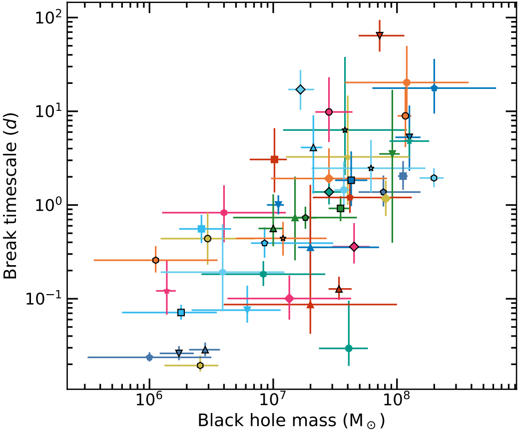

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- When accounting for error bars on $M_{\rm BH}$, $L_{\rm bol}$, t_b:

  $A \sim 1.5$, $B \sim 0.5$ and $C \sim -1.9$

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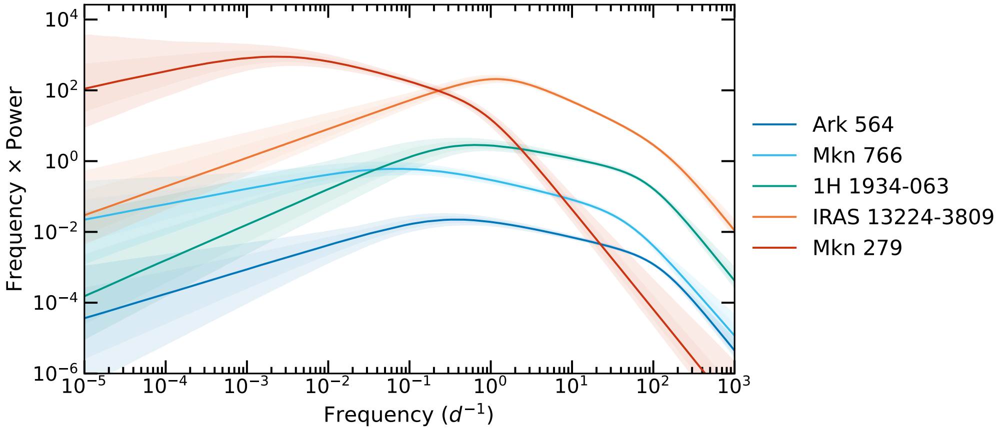
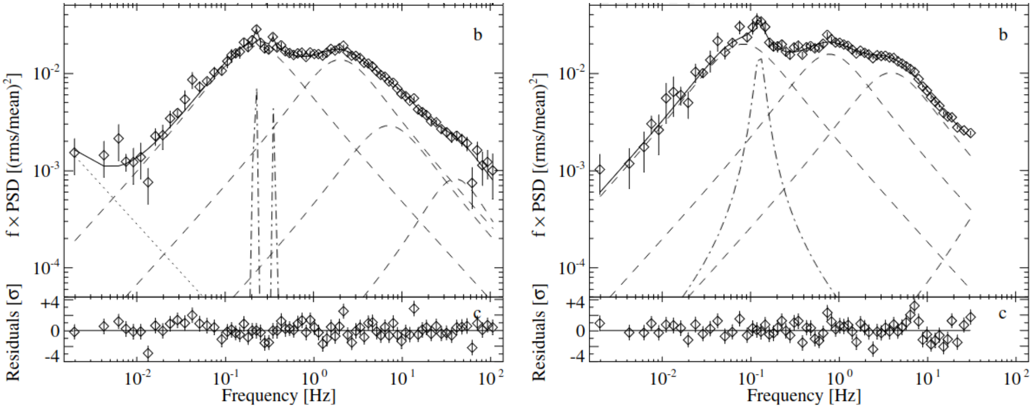
- MCG 6-30-15 could have a second bend (Nowak&Chiang+2000) but disputed by Uttley+2002, and is not significant in Kelly+2011

Sources with strong evidence for a second bend ($BF > 50$)



Amplitudes are rescaled for plotting purposes.

The case of an X-ray binary: Cygnus X-1 in its hard state



Power spectra of Cygnus X-1 from Pottschmidt+2003

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Thank you for listening!

Timescales in an accretion disc (α-disc)

For black hole mass of $M = 10^7 M_\odot$, at a radius $R = 10R_g$:

- Dynamical timescale: $t_{\rm dyn} \sim \sqrt{R^3/GM} \sim 25$ minutes
- Thermal timescale: $t_{\rm th} \sim \frac{1}{\alpha} t_{\rm dyn} \sim 4$ hours $(\alpha = 0.1)$
- Viscous timescale: $t_{\rm visc} \sim \frac{1}{\alpha}\left(\frac{R}{H}\right)^2 t_{\rm dyn} \sim 5$ years $(H/R = 10^{-2})$

We observe $t_{\rm break} \sim 0.5$ day, in the X-ray power spectrum

Propagating fluctuations in accretion discs

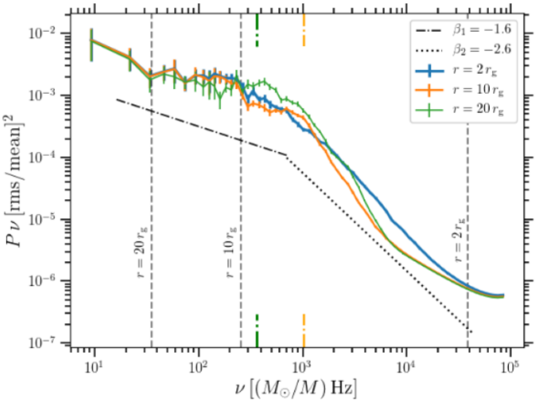
❶ Lyubarskii+1997: adding small random perturbations to α, creates fluctuations in the local accretion rate at different radii, which propagate inwards: $\mathscr{P}(f) \propto 1/f$

source of X-ray emission $\neq$ source of X-ray variability

❷ Uttley+2005: perturbations in the mass accretion rate should be multiplicative to reproduce the log-normal distribution of X-ray light curves.

Physical models: magnetic fields?!

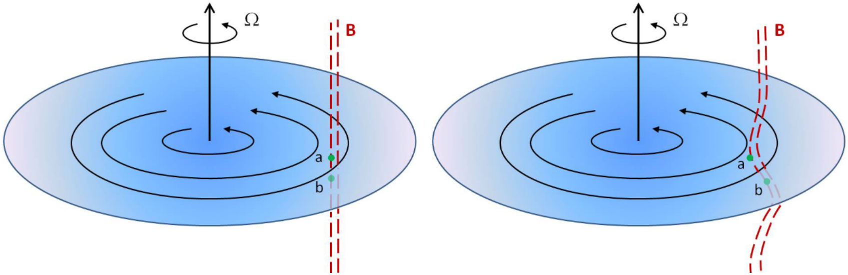
Bollimpalli+2020: full GRMHD simulations, somewhat realistic power spectrum



Periodogram of simulated time series of $\dot{m}$ from Bollimpalli+2020

Physical models: magnetic fields?!

Magneto-rotational instability (MRI) (Balbus&Hawley+1991) in a weakly magnetised disc can generate turbulence which could produce fluctuations propagating through the disc.



Magnetic field line deformation in the MRI instability. Credits: A. Mignone